A Hierarchical Visualization Tool to Analyse the Thermal Evolution of Construction Materials

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Abstract. This paper proposes a new visualization tool based on feature selection and the identification of underlying factors. The goal of this method is to visualize and extract information from complex and high dimensional data sets. The model proposed is an extension of Maximum Likelihood Hebbian Learning based on a family of cost functions, which maximizes the likelihood of identifying a specific distribution in the data while minimizing the effect of outliers. We present and demonstrate a hierarchical extension method which provides an interactive method for visualizing and identifying possibly hidden structure in the dataset. We have applied this method to investigate and visualize the thermal evolution of several frequent construction materials under different thermal and humidity environmental conditions.

1 Introduction

We introduce a novel method which is closely related to exploratory projection pursuit. It is an extension of a neural model based on the Negative Feedback artificial neural network [2]. This method is called Maximum-Likelihood Hebbian learning (ML) [3, 6, 5].

In this paper we provide a hierarchical extension to the ML method. This extension allows a dynamic investigation and visualization of a data set in which each subsequent layer extracts structure from increasingly smaller subsets of the data. The method reduces the subspace spanned by the data as it passes through the layers of the network therefore identifying the lower dimensional manifold in which the data lies.

The Negative Feedback neural network has been linked to the statistical techniques of Principal Component Analysis (PCA) [2], Factor Analysis [1] and Exploratory Projection Pursuit (EPP) [4]. The originality of this paper is the development and application of Hierarchical Maximum Likelihood Hebbian Learning (HML) to provide a novel approach.

Y. Luo (Ed.): CDVE 2004, LNCS 3190, pp. 238-245, 2004.

2 A Family of Learning Rules

Consider an N-dimensional input vector, $\mathbf{x}$, and a M-dimensional output vector, $\mathbf{y}$, with W_{ij} being the weight linking input j to output i and let η be the learning rate.
The initial situation is that there is no activation at all in the network. The input data is fed forward via weights from the input neurons (the $\mathbf{x}$ -values) to the output neurons (the $\mathbf{y}$ -values) where a linear summation is performed to give the activation of the output neuron. This can be expressed as:

$$y_i = \sum_{j=1}^{N} W_{ij} x_j, \forall i \quad (1)$$

The activation is fed back through the same weights and subtracted from the inputs (where the inhibition takes place):

$$e_j = x_j - \sum_{i=1}^{M} W_{ij} y_i, \forall j \quad (2)$$

After that, a learning rule is performed between input and outputs:

$$\text{Weight change: } \Delta W_{ij} = \eta . y_i . sign(e_j) | e_j |^{p-1} \quad (3)$$

This architecture is called Maximum Likelihood Hebbian Learning [3, 6, 5]. It is expected that for leptokurtotic residuals (more kurtotic than a Gaussian distribution), values of $p<2$ would be appropriate, while for platykurtotic residuals (less kurtotic than a Gaussian), values of $p>2$ would be appropriate.
By maximizing the likelihood of the residual with respect to the actual distribution, the learning rule is matched to the pdf of the residual. Maximum Likelihood Hebbian Learning (ML) [3, 5, 6] has been linked to the standard statistical method of EPP [4, 6].

3 A Hierarchical Extension of the Model

There may be cases where the structure of the data may not be captured by a single linear projection. In such cases a hierarchical scheme may be beneficial.
This can be done in two ways, firstly by projecting the data using the ML [3, 5, 6] method, select the data points which are interesting and re-run the ML network on the selected data. Using this method only the projections are hierarchical.
A second more interesting adaptation is to use the resulting projected data of the previous ML network as the input to the next layer. Each subsequent layer of the network identify structure among fewer data points in a lower dimensional subspace.